# Unsupervised Stem-based Cross-lingual Part-of-Speech Tagging for Morphologically Rich Low-Resource Languages

**Anonymous ACL submission**

## Abstract

Unsupervised cross-lingual projection for part-of-speech (POS) tagging relies on the use of parallel data to project POS tags from a source language for which a POS tagger is available onto a target language across word-level alignments. The projected tags then form the basis for learning a POS model for the target language. However, languages with rich morphology often yield sparse word alignments because words corresponding to the same citation form do not align well. We hypothesize that for morphologically complex languages, it is more efficient to use the stem rather than the word as the core unit of abstraction. Our contributions are: 1) we propose an unsupervised stem-based cross-lingual approach for POS tagging for low-resource languages of rich morphology; 2) we further investigate morpheme-level alignment and projection; and 3) we examine whether the use of linguistic priors for morphological segmentation improves POS tagging. We conduct experiments using six source languages and eight morphologically complex target languages of diverse typologies. Our results show that the stem-based approach improves the POS models for all the target languages, with an average relative error reduction of 10.3% in accuracy per target language, and outperforms the word-based approach that operates on three-times more data for about two thirds of the language pairs we consider. Moreover, we show that morpheme-level alignment and projection and the use of linguistic priors for morphological segmentation further improve POS tagging.

## 1 Introduction

Low-resource languages lack annotated data even for basic syntactic information such as parts of speech (POS). To address this problem, two main unsupervised approaches have been adopted: zero-shot model transfer (Pires et al., 2019) and cross-lingual POS tagging via alignment and projection (Yarowsky et al., 2001; Fossum and Abney, 2005; Das and Petrov, 2011; Duong et al., 2013; Täckström et al., 2013; Agić et al., 2015, 2016; Buys and Botha, 2016; Eskander et al., 2020b). Eskander et al. (2020b) show that the alignment and projection approach is less sensitive to the morphological dissimilarities between the source and target languages than zero-shot model transfer.

In annotation projection, the word structure in the source and target languages impacts the quality of the alignment and projection phases, and hence affects the overall performance of the ultimate POS model. This becomes a concern for languages with rich word structure where affixation is common as they usually suffer from sparse alignment models that often fail to align words corresponding to the same citation form due to the extensive paradigms and translation inconsistencies. Sparse alignment hinders the ability of a system to project the tags properly and results in null tags on the target side. These null tags then reduce the number of qualifying training examples and impact the POS model by introducing non-continuous labeled sequences. Adding to these practical issues, the concept of word as a unit of structure has long been questioned in language sciences (Marantz, 2001).

We hypothesize that using the stem as the core unit of abstraction results in better POS models for low-resource languages of rich morphology. Our contribution is three-fold.

*Unsupervised stem-based cross-lingual approach for POS tagging for morphologically complex low-resource languages*, where we use the stem as the core unit of abstraction. In order to adapt a fully-unsupervised approach, we use a state-of-the-art unsupervised morphological segmenter, MorphAGram (Eskander et al., 2016, 2020a), to derive the stems and morphemes. We follow the setup of Eskander et al. (2020b) using the Bible as the only source of parallel data in order to emulate a low-resource scenario. We experiment with

the same six source languages, namely English, Spanish, French, German, Russian and Arabic, but choose six morphologically complex target languages, namely Amharic, Basque, Finnish, Indonesian, Telugu and Turkish and add two new target languages, namely Georgian and Kazakh. For the latter we contribute a small POS-annotated dataset. We show that the stem-based approach outperforms the word-based one in 43 language pairs out of 48, with an average relative error reduction of 10.3% in accuracy per target language, up to 21.0% in the case of Kazakh. We also show that the stem-based approach outperforms the word-based approach which operates on three-times more data for about two thirds of the experimental pairs.

*Morpheme-level alignment and projection*, which allows for abstracting away from how the morphemes are combined in the source and target languages. We test the setup with Arabic as the source language and show improvements for seven out of the eight target languages.

*Using linguistic priors in morphological segmentation* , which results in better segmentation models towards better alignment and projection. Using Georgian as a case study, we show that the use of linguistic priors, in the form of a set of affixes provided by an expert in the target language, improves the ultimate POS models.

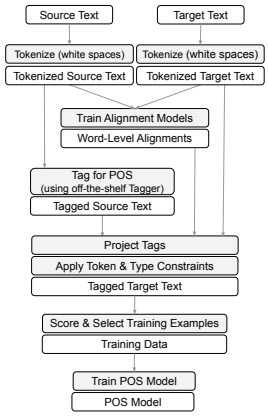
We plan to make the code and data available upon publication.

## 2 Approach

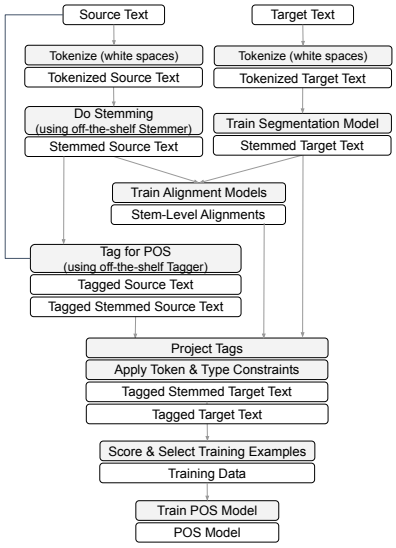
We perform fully unsupervised cross-lingual POS tagging via alignment and projection. We follow the main architecture presented by Eskander et al. (2020b) (Section 2.1). A primary difference is that we harness unsupervised morphological segmentation to use the stems as the core unit of abstraction for both alignment and projection (Section 2.2). In addition, we experiment with morpheme-level alignment and projection (Section2.3) and examine the use of linguistic priors towards better morphological segmentation and POS tagging (Section 2.4). This allows for less sparse alignment models and denser projections, which in turn produces larger POS training data of a better quality.

### 2.1 Word-based Alignment and Projection

Figure 1a shows the pipeline presented by Eskander et al. (2020b). The only input to the process is a parallel text between the target language and




(a) Word-based approach (Eskander et al., 2020b)

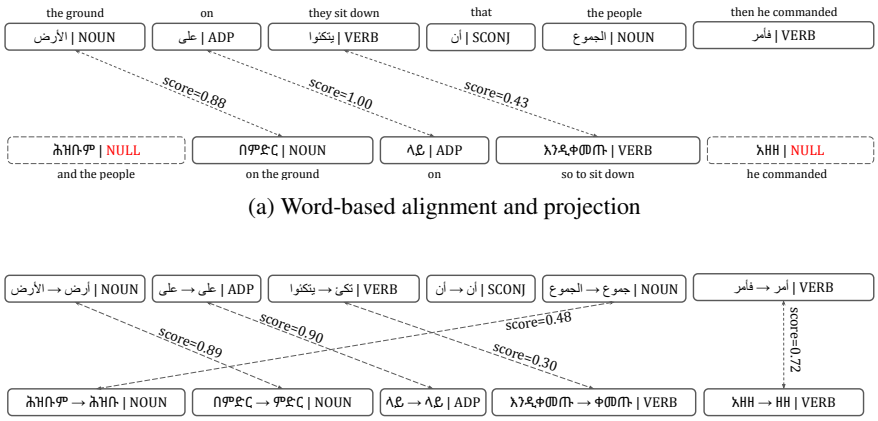



(b) Our proposed stem-based approach

Figure 1: Unsupervised cross-lingual POS tagging via alignment and projection

a source one for which a POS tagger is accessible. First, the parallel text gets white-space tokenized and is utilized to train two word-alignment models (one in each direction) that align the source and target sides on the word level. Next, the source side is tagged for POS using an off-the-shelf tagger (e.g., Stanza (Qi et al., 2020)). The source tags are then projected onto the target across word-based alignments, where only those bidirectional alignments whose confidence is above a particular threshold are considered in order to eliminate one-to-many and many-to-one alignments and those alignments of low confidence.

The projected tags for each token represent what are called token constraints, while the tag distribution of each word type across the whole target side forms type constraints. The token and type constraints are then coupled by nullifying those




(a) Word-based alignment and projection

(b) Stem-based alignment and projection

Figure 2: An example of alignment and projection from Arabic onto Amharic. The alignment models are trained on the New Testament. Arabic reads right to left.

tag assignments whose type-level probabilities are below some threshold. The target text, along with its projected tags, then constitutes the training data for a neural POS tagger, where only the top scoring sentences, in terms of tag-assignment density and alignment confidence, are considered.

The neural tagger is a bidirectional long short-term memory (BiLSTM) model (Hochreiter and Schmidhuber, 1997) that uses a custom softmax activation to handle the null tags. It uses word embeddings, both randomly initialized and the contextual multilingual embeddings *XLM-R* (Conneau et al., 2019); prefix and suffix n-gram character embeddings, where $n$ is in $\{1, 2, 3, 4\}$; and hierarchical Brown-cluster (Brown et al., 1992) embeddings.

The architecture can benefit from parallel data of multiple source languages, where either the projections from multiple source languages ($Mul\_proj$) or the decoded outputs that are based on multiple single-source models ($Mul\_out$) can be combined through maximum-voting mechanisms.

## 2.2 Stem-Based Alignment and Projection

While the architecture by Eskander et al. (2020b) yields the state-of-the-art results for unsupervised POS tagging when evaluated on 12 languages of diverse typologies, the complexity of word structure in the source and target languages has a direct impact on the quality of both alignment and projection. Rich word structure where affixation is common increases the ratio of word types to word tokens, which in turn results in sparse alignment models and incomplete projections that form null tags on the target side. Null tags result in a score that is too low for the underlying sentence to qualify as a training example and introduce missing information for the training of the POS model, which negatively impacts the overall quality of POS tagging.

An example is shown in Figure 2a, where Arabic and Amharic are the source and target languages, respectively. The example corresponds to verse *MAT 15:35*, *"He commanded the multitude to sit down on the ground"*, where the word-alignment models are trained on the New Testament. As shown, the two Arabic-Amharic pairs {ሕዝቡም, الجموع} (*and the people*, *the people*) and {አዘዘ, فأمر} (*he commanded*, *then he commanded*) are not aligned, resulting in null tags. The sparse word-alignment models are simply unable to properly align words that correspond to the same citation form because of the extensive paradigms, which, along with translation inconsistencies, leads to the loss of the one-to-one correspondence between word structures across parallel texts (examples are shown in Table 1). Using the stem instead of the word as the core unit of abstraction is more productive; the stem is usually shared by all the members of a paradigm, which reduces misalignment.

Figure 2b shows that stemming the Arabic and Amharic texts yields complete one-to-one alignments and projections, which in turn eliminates the word-based null assignments and assigns each word on the Amharic side a valid POS tag.

Figure 1b illustrates our overall stem-based approach. We first stem the source and target sides and train two stem-level alignment models, one in

| Verse | Amharic Word | | Arabic Word | |
|---|---|---|---|---|
| MAT 15:35 | ሕዝቡም | (*and the people*) | الجموع | (*the people*) |
| MAT 26:55 | ለሕዝቡ | (*to the people*) | للجموع | (*to the people*) |
| LUK 9:11 | ሕዝቡም | (*and the people*) | فالجموع | (*and the people* |
| LUK 23:4 | ለሕዝቡ | (*to the people*) | والجموع | (*and the people*) |
| MAT 1:24 | እንዳዘዘው | (*as he commanded*) | أمره | (*he commanded him*) |
| MAT 15:35 | አዘዘ | (*he commanded*) | فأمر | (*then he commanded*) |
| b.LUK 5:14 | እንዳዘዘ | (*as he commanded*) | أمر | (*he commanded*) |
| b.ACT 21:34 | አዘዘ | (*he commanded*) | أمر | (*he commanded*) |

Table 1: Paired inflected forms that correspond to the same citation form across Arabic and Amharic parallel verses in the New Testament

each direction. Next, we assign the stems of the source side the POS tags of their corresponding words, which are then projected onto the target stems through the stem-level alignments. We then apply the token and type constraints on the labeled stems on the target side. However, since we train the ultimate POS model on the word level, we replace each target stem by its corresponding word and assign that word the stem-based projected POS tag. The rest of the pipeline for sentence selection and training the POS model are the same as in the word-based architecture described in Section 2.1.

We assume that the source language is a high-resource one for which an off-the-shelf stemmer is accessible. On the other hand, for the target languages, we use MorphAGram [1](Eskander et al., 2020a) to train an unsupervised morphological segmentation model using the target side of the parallel text. MorphAGram is a state-of-the-art framework for unsupervised morphological segmentation based on Adaptor Grammars (AGs) (Johnson et al., 2007), nonparametric Bayesian models that generalize Probabilistic Context Free Grammars (PCFGs). We run MorphAGram in a cascaded setup of two learning rounds. In the first round, we train a segmentation model using a language-independent high-precision grammar (PrStSu2a+SM [2]) to obtain a list of morphemes. We then seed these morphemes into the best performing language-independent grammar (PrStSu+SM) for the second round of learning as described by Eskander et al. (2016, 2020a). Both PrStSu2a+SM and PrStSu+SM grammars model the word as a sequence of prefixes, a stem and suffixes, where the affixes are recursively defined in order to model multiple consecutive items.

[1]https://github.com/rnd2110/MorphAGram

[2]See Eskander et al. (2020a) for grammar definitions.

## 2.3 Morpheme-Based Alignment and Projection

Next, we perform morpheme-based alignment and projection in a similar fashion as in the stem-based approach (Section 2.2). This approach abstracts away from whether the morphemes in the source and target languages are free-standing or not.

On the source side, each morpheme receives a separate POS tag using an off-the-shelf POS tagger. These tags are then projected onto the target morphemes through bidirectional morpheme-level alignments. We obtain the target morphemes using MorphAGram, where the output of the PrStSu+SM grammar yields prefixes, a stem, and suffixes for each word. However, since we train the POS model on the word level, we replace each sequence of morphemes on the target side by its corresponding word and assign that word the POS tag of the representative morpheme. We define the representative morpheme either as the morpheme whose POS tag ranks the highest among those of the other morphemes [3] (RANK) or as the stem morpheme (STEM).

## 2.4 Using Linguistic Priors for Segmentation

We hypothesize that better detection of stems yields more robust alignment and projection towards improved POS tagging. Accordingly, instead of conducting morphological segmentation on the target side in a fully unsupervised manner, we follow Eskander et al. (2021) by seeding affix morphemes into the grammar tree prior to training the segmentation model; these affixes are generated manually by an expert in the target language. With Georgian as a case study, we examine this setup in the stem-based approach using the PrStSu+SM grammar.

## 2.5 Featurizing Segmented Data

In this setup, we utilize the unsupervised morphological-segmentation model that is trained on the target side of the parallel text to produce stem, complex-prefix and complex-suffix features, and leverage these features as part of the neural POS model. For training, we use these features as randomly initialized embeddings that we concatenate with the existing word, affix and words-cluster embeddings prior to applying the BiLSTM encoding layer.

[3]We use the default POS ranking at https://github.com/coastalcph/ud-conversion-tools

## 3 Experiments and Evaluation

### 3.1 Languages and Data

We conduct our experiments on six source languages and eight target ones [4], for a total of 48 language pairs. We use the same source languages used by Eskander et al. (2020b), namely English, Spanish, French, German, Russian, and Arabic, and experiment with eight typologically diverse target languages: six morphologically rich languages that are largely agglutinative, namely Basque, Finnish, Georgian, Kazakh, Telugu, and Turkish; morphologically rich Amharic, where many morphological alterations rely on consonantal roots; and less morphologically rich Indonesian.

We conduct the experiments in a truly low-resource scenario, where we use the New Testament as the source of our parallel data (unless noted otherwise): limited in size and out-of-domain with respect to the evaluation sets. We use the Multilingual Parallel Bible Corpus [5] (Christodouloupoulos and Steedman, 2015) as the source of data for all the languages, except for Georgian and Kazakh [6].

### 3.2 Experimental Settings

For the tagging of the source languages, we use the same off-the-shelf taggers as in Eskander et al. (2020b): Stanza [7] (Qi et al., 2020) for English, Spanish, French, German and Russian and MADAMIRA (Pasha et al., 2014) for Arabic. We also use MADAMIRA for Arabic morphological segmentation. For the stemming of the other source languages, we use the *Snowball* Stemmer (Porter, 2001) as part of *NLTK* [8] (Bird and Loper, 2004). On the other hand, we use MorphAGram [9] (Eskander et al., 2020a) to train and apply the morphological-segmentation models for the target languages as described in Section 2.2.

We also follow Eskander et al. (2020b) by using the same thresholds for alignment and projection, along with the same neural hyperparameters of the POS tagger. Finally, we evaluate out models in terms of POS accuracy on the same Universal Dependencies (UD) v2.5 (Zeman et al., 2019) test datasets. However, since the UD project does not currently contain Georgian datasets, we developed a small POS dataset for Georgian (100 sentences) following the UD-tagging scheme. The sentences are taken from the Modern Georgian and Political texts sub-corpora of the Georgian National Corpus [10], and they are hand-tagged and carefully revised by a linguist who specializes in and speaks Georgian as a second language [11]. Finally, all the results are averaged over three runs.

### 3.3 System Performance

Table 2 reports the POS accuracy for the baseline word-based approach and our stem-based approach for all the 48 target-source language pairs using the New Testament as the source of parallel data. In addition, we report the results for the two multilingual setups $Mul\_out$ and $Mul\_proj$ per target language. The stem-based approach outperforms the word-based one in 43 language pairs and all the multilingual setups except $Mul\_proj$ in the case of Indonesian, which stands out in our language sample as the least complex in terms of morphology. The biggest improvement in the stem-based approach is achieved in the cases of Russian → Turkish, Russian → Kazakh, Spanish → Kazakh and Arabic → Georgian, with relative error reductions of 33.8%, 30.2%, 28.6% and 27.2%, respectively. When averaging across the sources (including the multilingual ones), Kazakh, Telugu and Turkish experience the highest relative error reductions of 21.0%, 12.1% and 12.1%, respectively. On the other hand, Russian and Arabic yield the highest relative error reductions of 16.3% and 15.6%, respectively, when averaging across the target languages, which is in line with the morphological complexity of the two languages.

Next, we evaluate the morpheme-based approach (Section 2.3). Table 3 reports the performance of the word-based, stem-based and morpheme-based approaches using Arabic as the source language since it is more morphologically complex than the other sources. The morpheme-based approach results in dense training instances as both alignment and projection are performed in a more fine-grained level compared to the word-based and stem-based approaches. It therefore improves POS tagging for all the target languages except Amharic, where Telugu benefits the most with relative error reduc-

[4] Although most of our target languages are high-resource ones, we use them in a simulated low-resource setup.

[5] http://christos-c.com/bible

[6] We collected the New-Testament texts for Georgian and Kazakh from https://github.com/cysouw/MissingBibleVerses.

[7] https://github.com/stanfordnlp/stanza

[8] https://www.nltk.org

[9] https://github.com/rnd2110/MorphAGram

[10] http://gnc.gov.ge

[11] We plan to make the dataset publicly available for research purposes upon publication.

| Target | Approach | Source for Unsupervised Learning | | | | | | | | Ave. Error Reduction |
|---|---|---|---|---|---|---|---|---|---|---|
| | | English | Spanish | French | German | Russian | Arabic | $Mul\_out$ | $Mul\_proj$ | |
| Amharic | Word-based | 75.9 | 74.9 | 75.5 | 76.4 | 72.1 | 72.6 | 76.6 | 78.0 | |
| | Stem-based | **79.6*** | **77.5** | **77.7** | **77.8** | **76.2** | **74.5** | **78.6** | **79.6** | 9.9 |
| Basque | Word-based | 67.3 | 64.6 | 65.8 | 66.7 | 61.7 | 55.6 | 66.4 | 67.1 | |
| | Stem-based | **69.1** | **70.4*** | **70.5** | **69.6** | **65.2** | **60.8** | **71.0** | **71.4** | 11.5 |
| Finnish | Word-based | 81.0 | 78.8 | 77.4 | 79.8 | 77.8 | 66.1 | 81.0 | 81.7 | |
| | Stem-based | **81.9** | **80.1** | **80.9*** | **82.3** | **79.0** | **70.3** | **82.4** | **82.9** | 8.8 |
| Georgian | Word-based | **82.8** | 80.1 | 80.2 | **82.5** | 83.1 | 71.2 | 83.6 | 84.3 | |
| | Stem-based | 82.0 | **(80.4)** | **81.0** | 82.2 | **83.4** | **79.0*** | **84.3** | **84.7** | 4.4 |
| Indonesian | Word-based | 82.3 | **81.6** | **81.0** | 77.1 | 76.8 | 69.8 | 80.9 | **81.7** | |
| | Stem-based | **(82.5)** | 81.0 | 80.1 | **(77.3)** | **81.2*** | **72.3** | **81.4** | 81.0 | 2.5 |
| Kazakh | Word-based | 73.6 | 64.7 | 67.3 | 68.9 | 62.1 | 63.6 | 69.7 | 70.3 | |
| | Stem-based | **76.4** | **74.8** | **75.5** | **73.2** | **73.6*** | **70.8** | **75.3** | **76.7** | 21.0 |
| Telugu | Word-based | 76.7 | 68.4 | 67.9 | 70.4 | 63.5 | 59.5 | 68.6 | 71.3 | |
| | Stem-based | **78.6** | **72.7** | **72.2** | **71.9** | **69.6** | **66.8** | **72.9*** | **73.8** | 12.1 |
| Turkish | Word-based | **73.9** | 70.1 | 70.5 | 69.2 | 66.2 | 64.7 | 71.0 | 73.3 | |
| | Stem-based | 73.7 | **73.1** | **73.0** | **71.9** | **77.6*** | **71.9** | **75.4** | **73.6** | 12.1 |
| Ave. Error Reduction | | 5.0 | 10.4 | 10.5 | 6.8 | 16.3 | 15.6 | 10.6 | 7.1 | |

Table 2: POS-tagging performance (accuracy) of the word-based and stem-based approaches when using the New Testament as the source of parallel data. The best result per target-source pair is in **bold**. The highest relative error reduction in the stem-based approach per target language is marked by *. The stem-based improvements that are not statistically significant for $p\text{-}value < 0.01$ are between parentheses.

| Target Language | Approach | | | |
|---|---|---|---|---|
| | Word-Based | Stem-Based | Morpheme-Based (RANK) | Morpheme Based (STEM) |
| Amharic | 72.6 | **74.5** | 72.5 | 73.6 |
| Basque | 55.6 | 60.8 | 61.9 | **62.2** |
| Finnish | 66.1 | 70.3 | 73.8 | **74.2** |
| Georgian | 71.2 | 79.0 | **80.5** | 80.0 |
| Indonesian | 69.8 | 72.3 | 75.5 | **75.6** |
| Kazakh | 63.6 | 70.8 | 71.8 | **71.9** |
| Telugu | 59.5 | 66.8 | **74.7** | 71.8 |
| Turkish | 64.7 | 71.9 | 73.2 | **73.4** |

Table 3: POS-tagging performance (accuracy) of the word-based, stem-based and morpheme-based approaches when projecting from Arabic using the New Testament as the source of parallel data. The best result per target language is in **bold**. All the morpheme-based improvements are statistically significant for $p\text{-}value < 0.01$.

tions of 23.9% and 15.3% over the stem-based approach using the RANK and STEM mechanisms, respectively. The difference in the performance of the RANK and STEM mechanisms is only statistically significant for $p\text{-}value < 0.01$ in the cases of Amharic and Basque, where the STEM mechanism yields better performance, and in the case of Telugu, where the RANK mechanism is superior [12].

As mentioned earlier, we use Georgian as a case study to examine the impact of using linguistic priors for morphological segmentation on the quality of POS tagging (Section 2.4). The results are listed in Table 4. The use of linguistic priors improves the stem-based approach except when projecting from Arabic. The lack of improvement in the case of Arabic can be explained by over-segmentation that produces incorrect POS tags for the common conjunction და (*and*). The characters და also correspond to a verbal prefix that is manually seeded as a prior. This seeding causes erroneous projections labeling და as a verb or an adverb when projecting from Arabic.

Finally, we experiment with the use of the stem and affix information as training features in the POS neural model (Section 2.5). However, most of the improvements due to the use of these features are not statistically significant (See Appendix A for full results) since such features are surpassed by the prefix and suffix n-gram character embeddings.

### 3.4 Analysis of the Stem-Based Approach

Upon alignment and projection, the highest scoring target sentences are selected as training examples, where sentence score is defined as the harmonic

[12] The quality of morphological segmentation affects the detection of stems and thus affects the quality of the STEM mechanism.

| Target | Approach | Source for Unsupervised Learning | | | | | | | | Ave. Error Reduction |
|---|---|---|---|---|---|---|---|---|---|---|
| | | English | Spanish | French | German | Russian | Arabic | $Mul\_out$ | $Mul\_proj$ | |
| Georgian | Word-based | 82.8 | 80.1 | 80.2 | **82.5** | 83.1 | 71.2 | 83.6 | 84.3 | |
| | Stem-based | 82.0 | 80.4 | 81.0 | 82.2 | 83.4 | **79.0** | 84.3 | 84.7 | 4.6 |
| | LP Stem-based | **82.9** | **(80.8)** | **82.2** | (82.4) | **83.9** | 77.4 | **85.3** | **(85.1)** | 6.7 |

Table 4: POS-tagging performance (accuracy) of the word-based and stem-based (with and without linguistic priors (LP)) approaches when using the New Testament as the source of parallel data. The best result per source language is in **bold**. The improvements in the LP stem-based approach that are not statistically significant for $p\text{-}value < 0.01$ are between parentheses.

mean of the percentage of tokens with projected tags and the average alignment probability of those tokens. The fine-grained stem-level alignments allow for better alignment confidence and more dense sentences, which in turn increases sentence scores and the number of training examples, and hence reduces the number of out-of-vocabulary words (OOVs). Table 5 lists the average relative increase in sentence scores, average relative increase in the number of training instances and average relative decrease in the number of OOVs for each target language in the stem-based approach with respect to the word-based one. We witness improvements in the examined aspects for each target language, which explains the considerable improvements in the stem-based approach.

| Target | Ave. Sentence Increase | Ave. Score Increase | Ave. OOV Decrease |
|---|---|---|---|
| Amharic | 15.0 | 132.6 | 9.2 |
| Basque | 15.8 | 3.9 | 0.1 |
| Finnish | 6.9 | 5.5 | 0.7 |
| Georgian | 12.0 | 1.9 | 1.6 |
| Indonesian | 5.5 | 11.9 | 0.3 |
| Kazakh | 7.8 | 21.6 | 3.5 |
| Telugu | 2.8 | 14.1 | 0.7 |
| Turkish | 12.9 | 14.6 | 2.7 |

Table 5: Average relative increase in sentence scores and the number of training examples and average relative decrease in the number of OOVs per target language in the stem-based approach w.r.t. to the word-based one

Next, we examine the average relative error reduction in the detection of open-class tags (nouns, verbs and adjectives) in the stem-based approach as compared to the word-based one per target language (Table 6) and per source language (Table 7). Kazakh benefits the most from the stem-based approach at the detection of nouns and adjectives, while Amharic receives the highest gains for verbs. On the other hand, projecting from Russian in the stem space achieves the highest gains for nouns, while the stem-based projection from Arabic yields the highest gains for both verbs and adjectives.

| Target | Ave. Relative Error Reduction % | | |
|---|---|---|---|
| | Noun | Verb | Adjective |
| Amharic | 16.2 | 13.2 | 26.2 |
| Basque | 9.0 | 23.1 | 14.6 |
| Finnish | 13.0 | 16.6 | 15.8 |
| Georgian | 4.7 | 1.8 | 17.8 |
| Indonesian | 8.3 | 25.1 | 11.7 |
| Kazakh | 29.8 | 32.1 | 23.1 |
| Telugu | 17.4 | 23.7 | -1.1 |
| Turkish | 26.8 | 23.0 | 20.9 |

Table 6: Average relative error reductions for the detection open-class tags per target language

| Target | Ave. Relative Error Reduction % | | |
|---|---|---|---|
| | Noun | Verb | Adjective |
| English | 7.1 | 13.4 | 5.1 |
| Spanish | 16.5 | 25.2 | 15.2 |
| French | 12.7 | 25.5 | 16.9 |
| German | 9.5 | 11.0 | 22.8 |
| Russian | 21.3 | 21.2 | 25.7 |
| Arabic | 16.0 | 25.4 | 25.6 |

Table 7: Average relative error reductions for the detection of open-class tags per source language

Finally, Figure 3 illustrates the absolute improvements in POS tagging when applying the stem-based approach using the New-Testament as the source of parallel data compared to the word-based approach using the entire Bible as the source of parallel data (three-times more data). As illustrated, the stem-based approach achieves better performance in about two thirds of the language pairs with an average absolute gain of 1.7%. This means using the stem as the core unit of abstraction compensates for the lack of adequate parallel data.

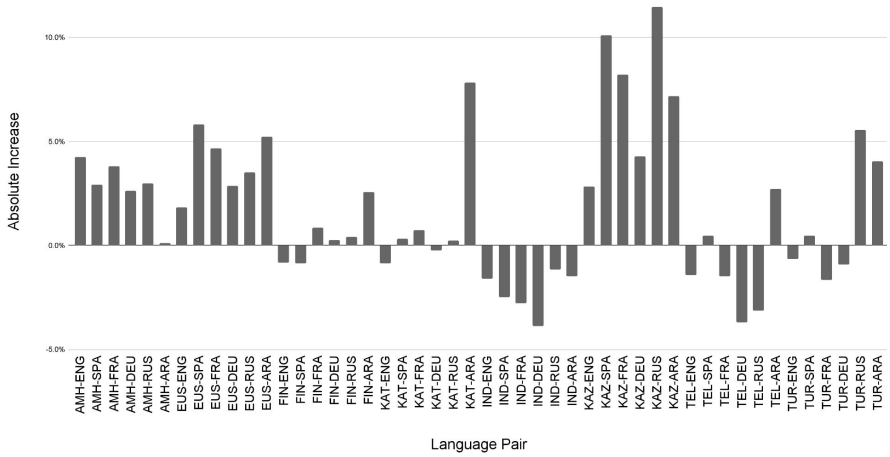



Figure 3: Absolute performance increases (accuracy) when applying the stem-based approach using the New Testament as the source of parallel data as compared to the word-based approach using the entire Bible as the source of parallel data

## 4 Related Work

The line of work most closely related to ours is unsupervised cross-lingual POS tagging via alignment and projection, which was first introduced by Yarowsky et al. (2001). They applied noise-reduction techniques to improve the alignments and used the resulting transition and emission probabilities to define an HMM POS tagger.

Exploiting multiple source languages via maximum voting was then explored by Fossum and Abney (2005), by voting among the outputs of different single-source models, and by Agić et al. (2015), by projecting the annotations from multiple languages before training the POS tagger.

In order to increase the size of the training data, Das and Petrov (2011) proposed graph-based label propagation, while Duong et al. (2013); Agić et al. (2015) applied self-training and revision. On another hand, Täckström et al. (2013) and Buys and Botha (2016) investigated the use of token and type constraints to reject projections of low confidence.

Eskander et al. (2020b) derived a cross-lingual POS-tagging pipeline that utilizes the best practices in alignment and projection. In addition, they examined the use of pretrained multilingual contextual embeddings within a rich neural architecture, which achieves the state-of-the-art results for unsupervised POS tagging. We follow their approach by presenting stem-based alignment and projection for morphologically complex low-resource languages.

Regarding unsupervised morphological segmentation, the two most notable frameworks are Morfessor (Creutz and Lagus, 2007; Grönroos et al., 2014), a commonly-used HMM framework that utilizes the MDL principle to segment into morphemes of a hierarchical structure, and MorphAGram (Eskander et al., 2020a), a segmentation framework that is based on Adaptor Grammars (AGs) (Johnson et al., 2007), Bayesian models that utilize Probabilistic Context Free Grammars (PCFGs). We use MorphAGram to train morphological-segmentation models as it achieves the state-of-the-art performance and allows for deriving affix and stem information (as opposed to a sequence of unlabeled morphemes).

## 5 Conclusion and Future Work

We presented a fully unsupervised stem-based approach for cross-lingual POS tagging via alignment and projection, where we use the stem as the core unit of abstraction to abstract away from complex affixation. Our experiments using six source languages and eight morphologically rich target languages in low-resource setups show improvements over the word-based approach in 43 language pairs out of 48, with an average relative error reduction of 10.3% in accuracy per target language. In addition, we examined morpheme-based alignment and projection and the use of linguistic priors in morphological segmentation, which further improve POS tagging. In the future, we plan to study how the linguistic aspects of the source and target languages impact cross-lingual learning, which allows for selecting the optimal sources for a given target.

## 6 Ethical Considerations

The Georgian annotations were done by a linguist with appropriate compensation after educating them about the research purpose and the annotation process. We claim ownership of the Georgian dataset for open distribution as the text is taken from the Modern Georgian and Political texts subcorpora of the Georgian National Corpus, which is an open-sourced work that allows for modifications, derived work and redistribution. The quality of the annotations was examined, both manually and empirically. The source code and the data will be released open-source. In addition, the funding agencies and all the contributors will be acknowledged in the final version of the paper. Finally, the limitations of the work lay within the reported performance. There should be no potential risks given these stated limitations.

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# A Appendix: Segmentation Information as Training Features

Table 2 shows the POS tagging results (accuracy) when using the stem and affix information as training features in the neural POS model, as described in Subsection 2.5.

| | | Source for Unsupervised Learning | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Target | Approach | English | Spanish | French | German | Russian | Arabic | $Mul\_out$ | $Mul\_proj$ |
| Amharic | Word-based | 75.9 | 74.9 | 75.5 | 76.4 | 72.1 | 72.6 | 76.6 | 78.0 |
| | Stem-based | 79.6 | 77.5 | 77.7 | **77.8** | 76.2 | 74.5 | 78.6 | 79.6 |
| | Stem-based + Stem Features | **(80.2)** | 77.5 | **(78.0)** | 77.6 | **(76.6)** | 74.6 | **78.7** | **79.7** |
| | Stem-based + Stem+Affix Features | 79.8 | **77.7** | 77.8 | **77.8** | 76.5 | **74.7** | **78.7** | 79.4 |
| Basque | Word-based | 67.3 | 64.6 | 65.8 | 66.7 | 61.7 | 55.6 | 66.4 | 67.1 |
| | Stem-based | **69.1** | 70.4 | 70.5 | **69.6** | 65.2 | 60.8 | **71.0** | 71.4 |
| | Stem-based + Stem Features | 68.7 | 70.5 | 70.5 | 69.3 | **(65.6)** | 60.3 | 70.9 | 71.6 |
| | Stem-based + Stem+Affix Features | 69.0 | **70.6** | **70.8** | 69.1 | (65.3) | **(62.0)** | 70.9 | **(71.8)** |
| Finnish | Word-based | 81.0 | 78.8 | 77.4 | 79.8 | 77.8 | 66.1 | 81.0 | 81.7 |
| | Stem-based | **81.9** | 80.1 | 80.9 | 82.3 | 79.0 | 70.3 | 82.4 | **82.9** |
| | Stem-based + Stem Features | **81.9** | **(80.4)** | 80.9 | **82.4** | **79.1** | (70.5) | **(82.7)** | 82.7 |
| | Stem-based + Stem+Affix Features | 81.8 | 80.1 | **(81.2)** | **82.4** | 78.9 | (70.6) | **(82.7)** | **82.9** |
| Georgian | Word-based | **82.8** | 80.1 | 80.2 | **82.5** | 83.1 | 71.2 | 83.6 | 84.3 |
| | Stem-based | 82.0 | 80.4 | 81.0 | 82.2 | **83.4** | **79.0** | 84.3 | 84.7 |
| | Stem-based + Stem Features | 82.1 | **80.5** | **(81.3)** | 82.1 | 83.3 | 78.7 | **84.4** | **(85.0)** |
| | Stem-based + Stem+Affix Features | 81.5 | 80.3 | 80.9 | 81.7 | 83.1 | 78.8 | 83.7 | 84.3 |
| Indonesian | Word-based | 82.3 | **81.6** | **81.0** | 77.1 | 76.8 | 69.8 | 80.9 | **81.7** |
| | Stem-based | **82.5** | 81.0 | 80.1 | 77.3 | 81.2 | **72.3** | **81.4** | 81.0 |
| | Stem-based + Stem Features | **82.5** | 80.8 | 79.9 | **(77.6)** | **81.3** | 71.7 | 81.1 | 80.9 |
| | Stem-based + Stem+Affix Features | **82.5** | 80.9 | 80.0 | 77.3 | 81.0 | 72.0 | 81.0 | 80.6 |
| Kazakh | Word-based | 73.6 | 64.7 | 67.3 | 68.9 | 62.1 | 63.6 | 69.7 | 70.3 |
| | Stem-based | 76.4 | 74.8 | 75.5 | **73.2** | **73.6** | **70.8** | 75.3 | 76.7 |
| | Stem-based + Stem Features | 76.3 | 74.8 | 75.7 | 72.8 | **(73.6)** | 70.7 | **75.4** | 76.5 |
| | Stem-based + Stem+Affix Features | **(76.6)** | **(75.2)** | **(75.8)** | 73.1 | **73.6** | **70.8** | 75.3 | **(76.8)** |
| Telugu | Word-based | 76.7 | 68.4 | 67.9 | 70.4 | 63.5 | 59.5 | 68.6 | 71.3 |
| | Stem-based | **78.6** | **72.7** | 72.2 | **71.9** | **69.6** | **66.8** | 72.9 | **73.8** |
| | Stem-based + Stem Features | 77.9 | 71.5 | **72.7** | **71.9** | **69.6** | 66.7 | 73.1 | 73.1 |
| | Stem-based + Stem+Affix Features | 78.4 | 72.4 | **72.7** | 71.4 | 68.7 | 67.1 | **(73.6)** | 73.7 |
| Turkish | Word-based | **73.9** | 70.1 | 70.5 | 69.2 | 66.2 | 64.7 | 71.0 | 73.3 |
| | Stem-based | 73.7 | **73.1** | 73.0 | **71.9** | **77.6** | **71.9** | **75.4** | 73.6 |
| | Stem-based + Stem Features | 73.5 | 73.0 | **73.1** | 71.5 | **77.6** | 71.7 | 75.1 | (73.7) |
| | Stem-based + Stem+Affix Features | 73.6 | 73.0 | **73.1** | 71.8 | **77.6** | 71.7 | 75.3 | **(73.9)** |

Table 8: Performance when featurizing segmentation output

# B Appendix: Hardware

We use a Google-Cloud virtual instance of 48 2.00GHz cores and 240GB of RAM to run all our experiments. The training rate is nearly 2,500 sentences per hour